Do Patents Increase Venture Capital Investments between Rounds of Financing? [a]

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Abstract

A long stream of research has documented the positive effects that patents bring about to emerging firms in high technology industries. The general consensus is that patents contribute to firm growth because they confer monopolistic market rights, offer protection from competitors, increase the negotiating position of patent holders and other benefits. What has received relatively less attention in the literature is whether patents act as a signal that attracts investors such as venture capital firms. The handful of studies that have addressed that question has not analyzed whether the signaling function of patents decreases after the initial attraction of venture capital, as information asymmetries between investors and target firms reduce. In this study, we draw upon a longitudinal dataset of more than 1500 U.S. – based biotechnology firms to empirically demonstrate that biotechnology firms with pending patent applications substantially increase the level of funding they receive for their first round of financing. In line with a reduction of information asymmetries once the initial investment has materialized, patent applications and granted patents have no effect on the growth of venture capital funds raised during the second round of financing. We conclude the study with a discussion of avenues for new research, implications for policy makers that consider the usefulness of the current patent system and with insights that can be employed by managers of firms in knowledge intensive areas such as biotechnology.

1. Introduction

Patents can contribute to the performance of firms through improvements in the rate of innovation, productivity and market value (Bloom and Van Reenen, 2002; Griliches, 1981; Hall, 2004; Hall et al., 2005). The linkage between patents and firm performance has been attributed largely to monopolistic market rights and future technology options, protection from competitors, and improvements in the negotiating position of patent holders with partners, investors and remaining stakeholders (Blind et al., 2006; Gans et al., 2002; Giuri et al., 2007; Harabi, 1995; Helmers and Rogers, 2011; Levitas and Chi, 2010; Silverman and Baum, 2002; Teece, 2000)[1].

A relatively less studied linkage between patents and firm growth is the value of patents as signals and situations where external investors, such as venture capital firms (VCFs), are attracted to firms with patents. Indeed, there are good theoretical reasons to expect such relationship (Graham et al., 2009; Heeley et al., 2007; Long, 2002). For instance, in knowledge intensive industries, the value of emerging firms that seek external finance can be difficult to evaluate because such firms often lack a track record and they are confronted with technical, scientific and regulatory challenges that are either unknown *ex ante* or difficult to tackle *ex post* (Harhoff, 2011). Ownership of patents, however, can signal the potential of a firm to external investors through possible future outcomes with commercial value (Hagedoorn et al., 2000; Heeley et al., 2007). Further, because patents confer monopolistic market rights, investors may place a market value on these rights and consequently invest in the firm that possesses them.

To corroborate such theoretical expectations a handful of empirical studies has documented that patents attract prominent VCFs, prompt VCFs to invest faster and generally increase the amounts invested in target firms (Audretsch et al., 2012; Baum and Silverman, 2004; Engel and Keilbach, 2007; Häussler et al., 2009; Hsu and Ziedonis, 2011; Mann and

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[1] On a macro level, patents have been associated with increasing national economic growth and the development and diffusion of knowledge (Blind and Jungmittag, 2008; Shapiro and Hassett, 2005).

Sager, 2007) [2]. In this literature, the effect of patents on venture capital attraction has typically been studied as a snap shot in time by focusing, for instance, on the amount of venture capital raised by a target firm over a certain period. As a result, what is largely unknown is whether the signaling value of patents in attracting VCFs diminishes over time as investors and target firms become more acquainted with each other. This inquiry is the point of departure for the present study.

To form our theoretical expectation we reflect upon the main arguments behind the relationship between patents and venture capital attraction. These arguments hinge, in large part, on a reduction of information asymmetries between VCFs and target firms. But, if such reduction lessens as VCFs and target firms become more familiar over time, then the value of patents in attracting venture capital investments should decrease. To study this proposition we leverage the tendency of VCFs to invest in target firms through sequential rounds of financing. Through such rounds, VCFs provide funds to a particular firm after it has met certain milestones that relate, mainly, to technical progress (Gompers, 1995). This sequential structure of VC investments allows us to detect patterns that would otherwise not be apparent. More specifically, each additional round of financing can typically reduce the information asymmetries between VCFs and the target firm because VCFs gather new information about the firm through monitoring, management and other forms of hands-on involvement in the firms they invest in (Gompers, 1995; Ruhnka and Young, 1987; Wang and Zhou, 2004). Accordingly, the effect of patents on attracting venture capital via a signaling process should diminish through sequential rounds of financing.

To test our theoretical expectations we employ a rich dataset that measures patent activity (granted patents and pending patent applications) from firm birth to the first round of financing and from the first round of financing to the second round for more than 1500 U.S.-based dedicated biotechnology firms (DBFs) that received funds from VCFs from 1974 to 2011. We focus our attention on the first two rounds of financing because in these rounds information

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[2] There is also evidence linking patents to successful Initial Public Offerings (e.g. Cockburn and MacGarvie, 2009; Heeley et al., 2007).

asymmetries between investors and target firms are expected to be potent. Therefore, by concentrating on these rounds we can detect the impact of information asymmetries on the effectiveness of patent activity as a signal. We focus on biotechnology because it is a knowledge intensive industry in which information asymmetries between investors and firms are expected to be significant (Janney and Folta, 2003). Corollary to the knowledge intensive character of the industry, patents are popular among biotechnology firms (Fligstein, 1996) and in fact evidence suggests that compared to firms in other high technology industries, investors weight patents more heavily in biotechnology when they decide to invest in a particular firm (Sichelman and Graham, 2010) perhaps because of the strong link between innovation and patents in that industry (Arundel and Kabla, 1998). Biotechnology is also an industry that receives large amounts of (staged) venture capital investments reflecting the risky nature of the industry as well as the potential for high returns (Baum and Silverman, 2004; Gompers and Lerner, 2001). Together, these industry characteristics suggest that if patent activity serves as a signal for investors whose value diminishes over time, evidence of such dynamics should be apparent across biotechnology firms.

For our empirical analysis, we construct models that associate patent activity before and after the focal round of financing with the amount invested per round to each firm and we control for regional and investing VCF-specific characteristics that may influence the growth of venture capital funds. To separate the function of patents as a signal from the value potential of patents, both of which can attract investors and capital, we account for the differential quality of patents. To isolate the strength of patents as a signal from other signals firms can employ, we include relevant control variables, such as the presence of distinguished scientists on the board of directors.

Our interest on the value of patents as signaling mechanism for capital investments in small firms and specifically on whether such value diminishes over time is motivated by more than academic curiosity. Answers to these questions have important policy implications. The number of patents and patent applications have increased substantially over the years (Kim and Marschke, 2004; Kortum and Lerner, 1999), but so have the costs associated with processing

patents. Such costs are instrumental in driving concerns over the usefulness of the current patent system, especially with regard to the degree that it puts smaller firms in a disadvantage and thus potentially hinders innovation (Bessen and Meurer, 2008; Jaffe and Lerner, 2004). Assessing whether patents increase private sector investments in small firms and whether such increase is affected by the familiarity between VCFs and target firms, needs to be taken into account when policy makers and other stakeholders consider the relevance of the current patent system.

We proceed with the rest of the paper as follows: In section 2 we review the literature on the functions of VCFs and how patents can act as signal and form our hypotheses. In sections 3 and 4 we present our methodology and data. In section 5 we present our results and we conclude in section 6.

2. How patents can act as signals to investors

In their most common form of arrangement, venture capital firms pool capital from institutional investors such as pension funds and university endowments. Using these capital pools VCFs, in turn, make investments and tie their compensation to the returns of their investments. Because theVCFs manage a rather small share of the funds maintained by institutional investors, the risk exposure of each institutional investor is relatively limited. Accordingly, VCFs can afford to invest in risky ventures that have the potential to yield returns above 25 percent so that they maximize their compensation as well as the compensation of the institutional investors (Zider, 1998).

A popular investment target for VCFs is young firms in high technology areas such as biotechnology. These firms have historically demonstrated a potential for high returns (Carpenter and Petersen, 2002) but they grapple with highly complex scientific problems associated long research cycles and challenging legal environments (DiMasi and Grabowski, 2007; Häussler and Zademach, 2007) that raise the risk they carry. Because of such conditions and of their young age, firms in such sectors typically find it difficult to generate current cash flows or establish a record of future cash flows. Accordingly, even when the target firm fully

understands its potential, it might still find it difficult to convey that potential to VCFs, which can create a mismatch of firm-specific information possessed by VCFs and by the target firm. As a result, the relationship between VCFs and target firms before an investment takes place is commonly prone to information asymmetries (Cumming, 2005; Sahlman, 1990).

To overcome such information asymmetries, firms seeking capital often use signals that partly substitute for the lack of an established record and can portray the potential of the firm (Busenitz et al., 2005; Certo et al., 2001; Zhang and Wiersema, 2009). In fact, whenever information asymmetries are present, VCFs tend to rely on signals of this sort before they make investment decisions (Amit et al., 1990; Higgins and Gulati, 2006) because *a priori* the separation of high-quality start-ups from firms with less potential can become prohibitively difficult (Davila et al., 2003). Along these lines, a number of studies demonstrate that, in general, signals can reduce information asymmetries (e.g. Cohen and Dean, 2005; Janney and Folta, 2003; Mishra et al., 1998).

The next relevant question then is whether patents can effectively act as such a signal. Strong signals need to be observable and costly to imitate (Cohen and Dean, 2005; Spence, 1973). Additionally, signals which are governed by strong institutions and hence conform to a certain institutional standard tend to increase in value (Janney and Folta, 2003). This holds largely because conformity typically reduces the variation among the signals and thus can alleviate the impact that the subjectivity of the receiver can bring to the valuation of the signal (Fischer and Reuber, 2007; Perkins and Hendry, 2005). Patents would therefore appear to meet the requirements for a signal because they are freely available (making them easy to observe), are costly to acquire (Graham et al., 2009) and are governed strictly. Particularly in the case of firms in knowledge intensive industries where information asymmetries are typically strong (Chaddad and Reuer, 2009) and, accordingly, signals are a major means to convey the market potential for a firm, patents have increased value for investment decisions (Sichelman and Graham, 2010) potentially because they relate to invention and often to innovation which in turn can lead to commercial gains (Acs et al., 2002; Arundel and Kabla, 1998; Griliches, 1998).

In line with the theoretical expectation that patents can act as a signal to investors, empirical evidence suggests that patents do serve such a function. Baum and Silverman (2004) found a positive association between the number of patents and patent applications for a focal Canadian biotechnology firm with the total amount raised by investors before the firm had an Initial Public Offering. Audretsch et al. (2012) surveyed nascent firms from a number of industries to conclude that firms with patents are more likely to attract external finance and Engel and Keilbach (2007) reached similar findings using a dataset of German young firms. Mann and Sager (2007) studied software development firms and reported a strong correlation between patents and a number of variables that measure attraction of venture capital, such as the number of financing rounds and the total amount of capital investment. Finally, Hsu and Ziedonis (2011) concluded that firms holding larger portfolios of patents were more likely to attract prominent investors for the first round of financing and Häussler et al. (2009), found that larger stocks of patent applications shortened the time that German and British biotechnology firms received venture capital financing for the first time.

Collectively, the abovementioned empirical studies have yielded insights backed up by statistical evidence that patents generally act as a signal to investors. What is difficult to infer from existing studies is whether and how the value of patents as a signal diminishes once the quality of the firm is assessed more closely by the investors. To answer this question we refer to the literature that analyzes how VCFs reduce information asymmetries once they have invested in a firm. The starting point of this literature is the basic insight that information asymmetries lead to agency problems (Fama, 1980; Jensen and Meckling, 1976). A major task of VCFs is therefore to reduce agency problems of this sort. A typical mechanism that VCFs use for this purpose is to provide funds in rounds of financing (Neher, 1999; Wang and Zhou, 2004). Under this mechanism, target firms receive funds of a particular round of financing conditional on having received funds (and having met certain milestones) of a previous round. Between rounds, VCFs become actively involved in the day-to-day operations of the target firm via consulting and monitoring (Gorman and Sahlman, 1989; Rosenstein et al., 1993). In doing so, VCFs follow the progress of the target firm, evaluate its prospects and generally get more

acquainted with the firm they have invested in. It follows that information asymmetries between VCFs and target firms should decrease under these conditions. In environments with reduced information asymmetries the value of signals tends to decrease (Gulati and Higgins, 2003; Higgins and Gulati, 2006). By extension, once a VCF is familiar with the target firm, the effectiveness of patents as signals that can attract additional funds is expected to be limited. Empirical studies have not however tested or quantified the extent to which such a decline does occur and in the next section we explain how we contribute to the existing literature by addressing the issues at hand.

3. Methods and Procedures

To empirically test the proposition that the signaling value of patents will tend to decline as capital investment in small firms proceeds in sequential rounds, we need to associate the patent activity of a firm with the growth of the venture capital it attracts while information asymmetries between investors and the firm diminish over time. We operationalize patent activity with the number of patents and patent applications the focal firm has been granted or filled respectively. To test whether the effectiveness of patent activity as a signal declines as a result of reduced information asymmetries we build two empirical models. In the first, patent activity is regressed on the sum of venture capital funds raised by a given firm at the first round of financing when information asymmetries are expected to be strong. In the second model, patent activity is regressed on the sum of venture capital funds raised by a given firm during the second round of financing at which time information asymmetries are expected to decline. Formally, the two models are specified as follows:

$$\ln(y_{ij=1}) = X_{ij=1}\beta + \varepsilon \qquad (1)$$

$$\ln(y_{ij=2}) = X_{ij=2}\beta + \varepsilon \qquad (2)$$

where the dependent variable y_{ij} is the natural log of the total amount of VC funding raised by biotechnology firm i at round j and X_{ij} is a vector of round-specific variables that can affect the growth of venture capital funds for a particular firm.

We include patent activity as an explanatory variable in both models and we capture patent activity with the number of patents and patent applications granted to and filed by a given firm. We separate granted patents from pending patent applications because their signaling values might differ in subtle but important ways (Gans et al., 2008; Popp et al., 2004). For instance, in contrast to granted patents, patent applications are open to revisions. The implication is that in highly evolving fields such as biotechnology, applicants often start with claims that are broad enough to create uncertainty for competitors, which in turn can discourage them from entering a particular research field (Harhoff and Wagner, 2009; Popp et al., 2004). Nevertheless, what is eventually patented is often the most fruitful area from the broad claims of a pending application (Popp et al., 2004) which suggests that granted patents can also carry significant value. It is therefore of interest to test whether the pull on capital is sensitive to the different advantages offered by granted patents and pending patent applications. Indeed existing evidence indicates that patent applications may have a stronger signaling effect than patents in attracting venture capital faster and at larger volume (Baum and Silverman, 2004; Häussler et al., 2009). For all these reasons, we consider these two forms of patent activity separately in our models.

For the first round of financing in (1) we measure patents and patent applications from firm birth until the date of financing and expect a positive sign for the corresponding coefficient. This would indicate that patent activity acts as a signal and increases the level of venture capital funds invested in the focal firm (*PatentApp_1* and *PatentGrant_1*). For the second round of financing we maintain our measures of patent activity in (1) and we also add two independent variables that measure the number of patents and patent applications granted or filled respectively from the date of the first round of investment until the date of the second round of investment (*PatentApp_2* and *PatentGrant_2*). We do so in order to test whether the

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strength of patent activity as a signal reduces over time as well as whether the timing of patent activity is sensitive to such considerations. In line with our discussion in section 2, we expect the patent activity before the second round of investment to have a diminished influence on the growth of venture capital funds invested in the focal firm.

In order to most effectively evaluate whether patents act as a signal that can attract venture capital funds, we need to account for the differential quality of patents as VCFs will tend to invest in firms with the highest quality of intellectual property and greater future value. We follow previous literature (Gambardella et al., 2008; Harhoff et al., 2003; Häussler et al., 2009; Trajtenberg, 1990) and we approximate patent quality with a variable that measures the average number of times the patents owned by the focal firm have been cited by other patents (i.e. forward citations) [3] (*PatentCiteYear_1*). Higher citation levels imply superior scientific significance or applicability and are used as indicators of higher quality patents. In (2), where we model the investments of the second round, besides *PatentCiteYear_1* we also include a similar variable that measures the forward citations of patents granted from the date of the first round until the date of the second round (*PatentCiteYear_2*). We expect patents of higher quality to attract greater amounts of funds in both investment rounds.

The patent activity of a focal firm before the first round of financing is by definition unaffected by the involvement of VCFs in the firm. But, the patent activity before the second round of investment can be influenced by managerial advice under the consulting role that VCFs assume once they invest in a firm. To account for such potential specification bias, we include in (2) the lagged dependent variable (i.e. the dependent variable in (1) which is the total amount invested in the first round of investment – *VCF_Investment_1*) (Baum and Silverman, 2004; Jacobson, 1990). Given that conditional on the receipt of funds, the amount per round

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[3] Note that the number of forward citations is not a measure that is fully observable by the VCFs when they invest in the firm because VCFs are able to observe only the citations that have been received by the time they invest. Further, more recent patents tend to receive fewer citations compared to older patents mainly due to the effective time a patent may need until it becomes visible. To account for this observation we divide the average number of forward citations for the patents of a given firm by the age of the patent measured in years (citations are measured up to early summer of 2012).

generally increases with more advanced rounds (Gompers, 1995), we expect a positive sign for this variable.

Besides patent activity, emerging firms without a proven track record can employ additional signals to convey their potential (Gulati and Higgins, 2003; Lee, 2001). Such signals tend to leverage the reputation of the team around the firm. For example, because firms in high technology industries usually center around their founding team (Arvanitis and Stucki, 2012; Gompers et al., 2010), the reputation and the previous business history of the founders are often used as signals (Audretsch and Stephan, 1996; Bonardo et al., 2011; Certo, 2003; Elitzur and Gavious, 2003). Similarly, habitual entrepreneurship can be presented as a signal of high human capital perhaps because previous firm founding experience can improve business recognition skills (Shane, 2000). Accordingly, both in (1) and (2) we include a variable that takes the value of 1 if one of the founders of the focal firm is a preeminent member of the academic community[4] and/or has started a firm previously (*FounderSignal*). Along the same lines, once the venture capital investment has been made, the eminence of the investors can also act as a signal under the premise that over time successful investors develop skills that allow them to effectively identify firms with potential (Casamatta and Haritchabalet, 2007; Sorenson and Stuart, 2001). By extension, in (2) we include a variable that depicts the Lee et al. (2011) reputation score of the highest ranked funding VCF of the first round of financing (*VCFreputation*_1). In line with the discussion in section 2, we expect *FounderSignal* to influence the total amount invested in the first round of financing and this effect to die off for the second round. For *VCFreputation*_1 we expect it to associate positively with the total venture capital amount raised in the second round of financing.

In addition to the signaling effect that funding VCFs can have, their availability of funds can also influence the growth of venture capital funds invested in a given firm. The availability of funds is determined in large part by the number of investors per firm and the size of each investor. VCFs with ample pools of capital usually invest higher amounts per target

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[4] We code an academic founder as eminent if she holds a distinguished and/or named professorship and/or is a member of the Academy of Sciences and/or has won a Nobel Prize.

firm (Gupta and Sapienza, 1992; Tian, 2011). At the same time, VCFs often co-invest in a target firm with other VCFs. Such co-investment schemes are often referred to as syndication and are used mainly in order to spread the risks that arise from investments in unproven firms (Lockett and Wright, 2001). As such, larger syndication arrangements can afford individual syndication members to invest higher amounts in the target firm. Overall, receiving funds from wealthier VCFs through syndication is expected to increase the total amount raised by a given firm. Accordingly, in (1) and (2) we include two variables that measure the number of investors per round as well as their average size and expect positive signs for both coefficients (*SyndicateInvestors1, SyndicateInvestors2, SyndicateSize1, SyndicateSize2*). Prompted by the division of labor in syndicates of VCFs (Ferrary, 2010) under which the most proximate VCF is usually the most heavily involved in the day-to-day operation of the target firm, the last variable we include in the empirical models that relates to the funding VCFs is the distance between the most proximate funding VCF and the target firm (*DistanceClosestVCF*). Spatial proximity between target firms and investors typically eases the monitoring functions of VCFs (Sorenson and Stuart, 2001; Zook, 2005) and can lead to higher investments (Tian (2011)). It follows that we expect a negative sign for the coefficient in question.

In addition to the signaling value of patents, their quality as well as the characteristics of the investors, the regional environment of the target firms can also influence the level of venture capital funds they might raise. Agglomeration externalities such as knowledge spillovers, pecuniary benefits (e.g. from a rich local labor pool) and network effects have been shown to positively influence a number of performance metrics of high technology firms including their growth of venture capital funds (Coenen et al., 2004; Gittelman, 2007; Kolympiris et al., 2011). Agglomeration economies of different strength may emanate from different organizations such as universities, firms in the same industry or firms in supporting industries (Döring and Schnellenbach, 2006; Kolympiris and Kalaitzandonakes, 2012). In this context then, we include in (1) and (2) five variables that account for such potential influences. Following previous literature that shows that the impact of universities spans up to the Metropolitan Statistical Area (MSA) level (Abel and Deitz, 2012; Anselin et al., 2000; Varga,

2000), we construct a variable that measures the number of universities that perform biotechnology related research and are located in the same MSA as the focal firm (*UniversitiesInMSA*). We expect the sign of this variable to be positive. To account for potential proximity effects from the presence of VCFs that arise from the knowledge that VCFs and their networks create (Gompers, 1995; Shane and Cable, 2002), we follow Kolympiris et al. (2011) and for each round of financing we construct two variables that measure the density of VCFs in 0 to 10 and 10 to 20 miles from the origin firm respectively (*VCFarea_0010_1, VCFarea_1020_1, VCFarea_0010_2, VCFarea_1020_2*) . To capture the benefits a given firm can reap from the proximity to overperforming firms in the same industry (Beaudry and Breschi, 2003), for each round of financing we include in (1) and (2) two variables that measure the number of patents granted to biotechnology firms located 0 to 10 and 10 to 20 miles from the origin firm before the focal financing round (*PATENTarea_0010_1, PATENTarea_1020_1, PATENTarea_0010_2, PATENTarea_1020_2*). We expect positive signs for the corresponding coefficients[5].

Finally, we include two additional control variables that can influence the growth of venture capital funds for a given firm in our models. The first measures the age of the focal firm at the round of financing (*Age1, Age2*). Older firms may have more experience and have survived for a longer time and these features might be evaluated positively by VCFs. At the same time, older firm age in conjunction with lack of previous financing may be taken as a negative signal by VCFs. Therefore, we do not form strong priors with regard to the direction the age of firms can move their growth of funds. The second control variable we include in our empirical specifications is a linear trend that assumes increasing values for rounds of financing that took place at later years. We construct two trend variables that correspond to each of the

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[5]Note that besides the regional characteristics we have already discussed, there can be qualitative and often unobserved regional features that can also affect the performance of a given firm and its subsequent growth of venture capital funds. These features can expand beyond the geographic boundaries of 10 or 20 miles and refer mainly to attitudes towards risky investments or the efficacy of state services or private consulting organizations (e.g. the Larta Institute or Foresight S&T) that can assist firms in improving their performance. Largely because of the qualitative nature of these factors, representing them through associated variables is a task with mounting difficulties. As we explain in detail in Section 5 we employ appropriate estimation techniques to account for such considerations.

rounds of financing we focus on (*Trend_1, Trend_2*). We include the linear trends to account

for the general increase of the size of venture capital investments over time and we expect

positive signs for *Trend_1* and *Trend_2*.

4. Data sources and presentation

To perform our empirical analyses, we began by measuring all venture capital

investments toward dedicated biotechnology firms (DBFs) from 1974 up to 2011using

Thomson Reuter's SDC Platinum Database (SDC) . We also sourced from SDC the address and

founding date of each DBF, the amount invested per round, the date of financing round, the

investors per round as well as their address and previous investments. We used this information

to construct our dependent variables and *Age1, Age2, SyndicateInvestors1, SyndicateInvestors2,*

SyndicateSize1, SyndicateSize2, DistanceClosestVCF, VCFarea_0010_1, VCFarea_1020_1,

VCFarea_0010_2, VCFarea_1020_2. For *DistanceClosestVCF, VCFarea_0010_1,*

VCFarea_1020_1, VCFarea_0010_2, VCFarea_1020_2 we needed to calculate the distance

between the target firm and investors and the density of VCFs in a region[6]. To do so, we

converted the addresses of target firms and VCFs to coordinates at http://batchgeo.com.

Subsequently, we plugged these coordinates in the distance formula[7] we employ and

constructed the corresponding variables.

For our independent variables (*PatentApp_1, PatentGrant_1, PatentApp_2,*

PatentGrant_2) we used Google Patents ® which indexes granted patents and pending patent

applications from the United States Patent and Trademark Office (UPSTO)[8]. We searched for

every granted patent and pending patent application where the focal firm was listed as the

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[6] The density of VCFs did not include the funding VCFs of the focal firm.

[7] We employed the general formula of the spherical law of cosines which corrects for Earth's spherical shape: $Distance_{12} = ar \cos(\sin(lat_1).\sin(lat_2)+\cos(lat_1).\cos(lat_2).\cos(long_2-long_1)) \times 3963$

[8] See http://www.uspto.gov/news/pr/2010/10_22.jsp for an official USPTO press release regarding its cooperation with Google Patents.

applicant/assignee[9]. Using the application and granted date we allocated patent activity between rounds. It is important to note that before November 29, 2000 there was no formal obligations for the publication of patent applications from the UPSTO[10]. Therefore, prompted by previous findings which suggest that 85 to 90 percent of patent applications turn into patents (Baum and Silverman, 2004; Quillen and Webster, 2001) and in order to include early years in the analysis we used two alternative approaches. In the first instance, patent applications before 2001 are approximated by multiplying the corresponding number of granted patents by 0.78. This fixed factor is the percentage of patent applications that turned into patents for applications filled before the second round of financing for applications after 2001 in our sample, the period where we had full information both on patents and patent applications. In the second instance, which we present in the Appendix, patent applications before 2001 are calculated through a linear extrapolation from a trend variable and an intercept that we estimated from regressing patent applications to a year trend. Both approaches yield qualitatively similar results, which adds confidence to our estimates[11].

To construct *PatentCiteYear_r1* and *PatentCiteYear_r2* we employed Google Patents ® and counted the number of times each of the patents in our dataset was cited by other patents. Then, for each firm we calculated the average number of citations across all granted patents of the firm. As noted in footnote 3, to account for the tendency of older patents to be cited more heavily, we divided the average number of forward citations for the patents of a given firm by the difference (in years) between early summer of 2012 (when the variable was constructed) and the date that the patent was granted.

To collect biographical information for the academic founders we visited the website of each firm and complemented this search with academic founders' biographies provided at their

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[9] In a number of cases the name of the applicant/assignee differed across patents as, for instance, "inc." was missing or it was replaced by "inc". To ensure that the validity of our measure was not prone to such issues we double-checked the number of patents using a number of variations of the name of each firm.
[10] See http://www.uspto.gov/news/pr/2001/01-13.jsp for the official announcement.
[11] Alternatively, we could opt for focusing our attention only on patenting activity that occurred after November 29, 2000. By adopting this approach we would implicitly assume that the signaling value of patenting activity would be confined to the years after 2000. But, we have no theoretical reasoning for such argument. In fact, as seen in Tables 2 and 3, the trend variable in the empirical results is highly significant, which suggests that timing is important for our application.

personal websites. Using these sources, firms whose founder(s) had started a firm previously and/or held a distinguished and/or named professorship and/or were a member of the Academy of Sciences and/or had won a Nobel Prize took the value of 1 in the *FounderSignal* dummy variable.

To build *VCFreputation_1* we first consulted the yearly reputation rankings of VCFs maintained at http://www.timothypollock.com/vc_reputation.htm (Lee et al., 2011). DBFs whose funding VCFs at the timing of the financing round were not ranked were coded as 0. DBFs whose highest ranked VCF was also the highest ranked of all VCFs were coded as 1. To illustrate how we calculated the between cases we provide an example under which the highest ranked VCF was ranked as 250th in the year in question. First, we divide 250 by 1000 (the total number of ranked VCFs) which yields 0.25 and then we subtract 0.25 from 1 to have 0.75, which is the value of the *VCFreputation_1* variable for this hypothetical example. Using the same methodology, if the highest ranked VCF was ranked 150th, the value of the *VCFreputation_1* variable would be 0.85. And so on.

To construct *UniversitiesInMSA* we used the list of recipient institutions of biotechnology-related research grants maintained at the website of the National Institutes of Health. We complemented this list with comparable listings from the Association of University Technology Managers and the Chronicles of Higher Education. All three sources had information on the main address of each institution and whenever information was missing we visited the website of each institution to collect the address. The addresses were then assigned to MSAs using the zip code-to MSA list provided by the U.S. Bureau of Economic Analysis.

Finally, to build *PATENTarea_0010_1, PATENTarea_1020_1, PATENTarea_0010_2,* and *PATENTarea_1020_2* we first visited the UPSTO website to measure the yearly total number of patents assigned to each DBF. Then, we summed over the patents that were granted before the focal round of financing to DBFs within 0 to 10 and 10 to 20 miles from the origin DBF (using the coordinates and the distance formula previously described).

Figure 1 displays the density of patents within a 20 miles radius from each of the firms in our dataset. Regions at the East and the West Coast tend to be the most dense areas of patent ownership, an observation that most likely reflects the intense spatial clustering of DBFs in the US (Kolympiris et al., 2011; Powell et al., 2002). As a case in point, the most intense 20 miles radius in our sample was observed in Redwood City, California. Biotechnology firms within this 20 miles radius hold 644 patents in total. Further, Figure 1 illustrates that our dataset draws from both urban and rural areas, which suggests that our results are not limited to DBFs located only at a certain region.

The density of VCFs in our dataset is illustrated in Figure 2 and it roughly overlaps with the density of patents presented in Figure 1. We also observe that VCFs tend to share the same locations with the DBFs in our sample a phenomenon that likely reflects the common strategy of VCFs to situate themselves close to their target firms.

Table 1 presents descriptive statistics of the variables used in the empirical models. Most DBFs in the dataset received $1 million for the first round of financing and $2 million for the second round of financing. Note that the standard deviation is significantly larger than the mean observed value which indicates the wide array of venture capital amounts invested in different firms. Most firms did not have any patent activity before the focal round of financing, but the standard deviation of the observed patenting activity surpasses the average of the observed values and suggests that some firms had a large number of patents and patent applications before the focal round of financing. This is an important observation because it indicates that our sample is composed of firms with varying degrees of patent activity and thus it alleviates concerns of overstressing the significance of patents that might result from the

potential tendency of better firms to patent more (Helmers and Rogers, 2011). Along the same lines, the majority of the patents granted to a given firm did not receive any citations per year.

Most of the firms in the dataset were older than 3 and 4 years old respectively when they received first and second round of financing while the average reputation score for the highest ranked funding VCF was 0.313 which translates to a yearly ranking of 687 out of 1000[12]. More than 100 firms in the dataset had a founder that was coded as conveying a signal of quality, while the majority of firms received funds from VCFs located within a 0.04 miles distance. DBFs received funds mostly from 1 VCF both in the first and the second round of financing and the average number of investors for the first and the second round of financing was 2.2 and close to 3, respectively. With regard to the size of the investors, on average they had invested around 300 million before providing financing to the firm in question.

With respect to the regional environment of the average focal firm, around 10 universities were located in the same MSA, roughly 16 VCFs were located in a 0 to 10 miles radius and approximately 11 VCFs in a 10 to 20 miles radius. Finally, the average DBF in our sample was surrounded by DBFs that in sum had been granted around 140 patents before the focal DBF received funds (approximately 90 patents were granted to firms in a 0 to 10 miles distance and roughly 50 patents were granted to firms in a 10 to 20 miles distance).

5. Empirical results

Tables 2 and 3 present the estimated coefficients for the models described in section 3. The heteroskedasticity test reported in Tables 2 and 3 shows evidence of heteroskedasticty and for this reason we use White's standard errors. We also test for the possibility that some of the errors in our models might be correlated. As discussed in footnote 5 there are often regional factors that are difficult to observe and which can affect the performance of all firms in a region or the capital investments they attract. For instance, such factors may include state subsidies and technical assistance for the development and financing of high technology firms and other such activities. Factors of this sort can therefore induce DBFs of a given state to overperform or

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[12] 1-(687/1000)=0.313

underperform jointly. If such influences do exist, the assumption of independence across observations for firms in the same state may be violated (Nichols and Schaffer, 2007; Stimson, 1985). To address this possibility we estimate (1) and (2) with standard errors of firms in the same state modeled as correlated (i.e. clustered at the state level)[13] and report those errors and the associated statistical significance in the last column of Tables 2 and 3. The estimated coefficients of the two models remain the same when estimating the two types of standard errors. Only the relative statistical significance of the estimated coefficients can change. Nevertheless, the statistical inferences from the two sets of standard errors are nearly identical and hence the models are robust to these alternative specifications.

The fit statistics reported at the bottom of Tables 2 and 3 indicate the joint significance of the variables in the empirical models and suggest that the fitted models have explanatory power. Finally, the multicollinearity condition index (20.12 and 24 for each model) is within limits and do not raise concerns about the presence of multicollinearity.

-----Tables 2 and 3 about here ----

Because the dependent variable is in logarithmic form, the estimated coefficients can be interpreted as semi-elasticities. In line with theoretical expectations, we find that patent activity serves as a signal that attracts venture capital investments but the attractiveness of that signal dies off once investors and target firms are more familiar with each other. In particular, one additional pending patent application before the first round of financing increases the amount of funds raised by a firm by 11.2 percent. This is a considerable increase especially when considering the 0 modal value for the *PATENTApp_1* variable and suggests that firms without patent activity generally receive significantly less funding from VCFs. To put the magnitude of the estimated coefficient in perspective, when evaluated at the average amount of first round funds observed in the sample (Table 1) the estimated coefficient indicates that one additional

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[13] The parameters and the standard errors are estimated with generalized estimating equations which is a method of calculating the standard errors by first estimating the variability within the defined cluster (in our application the state) and then sums across all clusters (Zorn, 2006).

pending patent application increases venture capital investments by more than $632,000[14] when

the modal value of the first round of financing is $1,000,000. When compared with the direct

costs of obtaining a patent, which typically range between $10,000 and $38,000 (Graham et al.,

2009; Lemley, 2000), the estimated signaling value of such a patent far surpasses these direct

costs. While this comparison is not meant to be a cost-benefit ratio for the acquisition of patents

by DBFs, our empirical results strongly suggest that the signaling value of patenting activity is

very significant and should be explicitly accounted for when firm strategy and public policy

consider the usefulness of patents.

Patenting activity does not appear to attract higher amounts of second round venture

capital investments, implying that a reduction of information asymmetries between investors

and target firms leads to a decrease in the signaling value of patent activity. Our empirical

results also suggest that while pending patent applications play an important signaling role , the

granted patents of a focal firm do not appear to attract additional funds neither in the first nor in

the second round of financing. This result is consistent with previous findings (Baum and

Silverman, 2004; Häussler et al., 2009) and might suggest that because claims in patent

applications can be broader than those ultimately allowed, they can magnify the potential of

young firms at early development stages. Finally, given that the impact of patent activity that

took place before the second round of financing is similar to the impact of patent activity that

took place after the second round of financing, it appears that the effectiveness of patent activity

as a signal to investors is not sensitive to when such activity originated.

Our empirical findings on the impact of forward patent citations may also explain the

insignificance of the granted patents as a signal. Specifically, we find that high quality patents,

as proxied by forward patent citations, attract greater amounts of capital. Therefore, VCFs

appear to invest larger amounts of capital in firms with patents of higher quality instead in those

with a large number of patents. Note that the quality of patents generated after the first round of

investment does not impact capital accumulation during the second round of investment. This

result suggests that patenting activity and patent quality have value as signals only during early

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[14] 0.112*5.65M (the average amount of first round funds reported in Table 1)=632,800

stage capital investments, when informational asymmetries are most signficant.

Other signaling mechanisms used by DBFs are also found important during the first round of financing and reductions of information asymmetries are once again found to diminish their effectiveness. In particular, DBFs founded by serial entrepreneurs and/or prominent academic scientist received, on average, 43 percent more capital during their first round of financing. They did not, however, enjoy a similar advantage in the second round of financing.

We did not find the reputation of the first round investors to influence the level of funding in the second round of investment for the DBFs in our sample. Indeed, most of the firms received funds from a single investor (Table 1), who in most cases was the main investor in the second round as well. As such, our finding may reflect this funding structure in our sample.

Our results on the influence of the syndication of investors are in line with theoretical expectations and recent literature findings (Tian, 2011). In particular, we find that investments by large groups of wealthy syndicated VCFs are associated with higher capital accumulation for a given firm. One additional VCF in the first round of financing raises the total venture capital amount of that round by 37 percent; the corresponding coefficient for the second round of financing was close to 25 percent. We draw similar conclusions about the influence of the size of the funding VCFs. In fact, for the second round of financing the characteristics of the funding VCFs are prime determinants of the venture capital funds invested in a given firm. Finally, we find that firms receiving funds from closely located VCFs receive, on average, less per round of financing. One additional mile in the distance between the target firm and the closest investor increases the total amount of financing by approximately 0.03 percent. This result is shaped, in some part, by the geographic distribution of VCFs and DBFs in our sample. Most of the firms in our sample source funds from VCFs located within walking distance and half of the firms receive funds from VCFs located less than 27 miles away (Table 1). As such, the average distance between target firms and VCFs reported in Table 1 (390 miles) is inflated somewhat by a small number of observations where East/West coast VCFs fund West/East coast DBFs in which typically larger VCFs provided significant amounts of finance to target

firms across the country. Consequently, while statistically significant, the effect of the

DistanceClosestVCF is expected to have a small overall economic effect for the majority of

firms in our sample.

For the variables that describe the regional environment around the focal firm, we find

that the density of universities in an MSA does not appear to influence the accumulation of

venture capital funds of DBFs in the region in either round of financing[15]. A higher number of

VCFs located in close proximity (within 10 miles) from a target DBFs is associated with a

higher amount of venture capital investment for the first round of financing but not for the

second round. It is possible that DBFs in early stages of development benefit from the

knowledge and experience of a dense local VCF network and such gains are reflected in their

level of financing. As DBFs mature, however, performance benefits from access to local

knowledge networks are not as pronounced and, as such, higher density of VCFs in close

proximity to DBFs does not influence their second round level of financing.   We similarly find

that the density of patents held by DBFs in close proximity (within 10 miles) from the target

DBF has a statistically significant positive impact on the amount of capital it receives during the

first round of financing but no impact during the second round. Overall, the coefficients of the

variables that characterize the regional knowledge environment where DBFs operate in our

models suggest that proximity effects are important for the level of financing of the DBFs.

Indeed, we find particularly interesting that such proximity effects appear to matter during the

first round of financing when firms are younger and less developed and less so during the

second round when firms are more developed and experienced; a finding that sides with

previous evidence that less established firms tend to benefit the most from proximity effects

(McCann and Folta, 2011). Hence, marginal agglomeration effects may be most pronounced in

the early stages of development of DBFs.

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[15] The *UniversitiesInMSA* variable is statistically significant only in one case where the standard errors
are clustered at the state level.

Finally, our control variables indicate that older firms receive more funds at the first round of financing and that over time capital investments in DBFs during both the first and the second round of financing have become larger.

6. Conclusion and discussion

A long stream of research has documented the positive effects that patents bring about to firms. The general consensus is that patents contribute to firm growth and survival because they confer monopolistic market rights, offer protection from competitors and enhance the negotiating position of patent holders. What has received relatively less attention in this literature is that patents can act as a signal to attract investors and capital. This type of effects are particularly important to emerging firms in knowledge intensive industries where long research cycles, scientific complexities and strict regulatory regimes make the development of a track record for a given firm difficult. In this context, signals that convey firm potential and quality can be of significant value. A handful of empirical studies that have taken up the issue in the past have shown that knowledge intensive firms which hold granted patents or have pending patent applications are more likely to receive larger venture capital investments faster. The dynamics of such signaling effects have not been investigated, however, and little is known about whether the signaling function of patents diminishes over time. In this study, we shed new light on the signaling function of patents in attracting investors by examining the strength of the signaling effects of patenting activity in sequential rounds of financing for small biotechnology firms.

Employing data from more than 1500 U.S.-based dedicated biotechnology firms, we examine whether the patent activity (granted patents and pending patent applications) of small biotechnology firms increases the amount of venture capital funds raised by such firms during their first and second round of financing. Our empirical results strongly corroborate theoretical expectations that patent activity before the first round of financing increases the capital invested in a firm. However, as firms mature and information asymmetries between them and investors decrease, the signaling value of patent activity diminishes and it does not affect the level of funds raised in the second round of financing. We also find that pending patent applications

rather than granted patents have a more significant signaling role. This finding potentially reflects the preference of VCFs to the opportunity that pending patent applications offer. Higher quality patents are also associated with higher amounts of capital investments. Finally, we find that the amount of venture capital funds raised by small biotech firms is also influenced by certain characteristics of the investors, such as size and syndication, as well as by proximity effects that allow firms to source knowledge from nearby institutions.

Our study has both scholarly and policy implications. For instance, we quantify the signaling value of patent activity and we find that, on average, an additional pending patent application is associated with an increase of more than $630,000 in the amount of venture capital funds raised in the first round of financing by small biotech firms. This valuation complements existing studies which estimate the value of patents but do not take into account the value of their signaling effect in attracting capital (Gambardella et al., 2008). The same finding however, has also important policy implications. Concerns have been frequently raised about the current status of the patenting system and about the degree it might hinder innovation, especially by placing young innovative firms at a disadvantage. Our findings, however, suggest that the signaling value of patenting activity alone exceeds typical direct costs of patent acquisition by 30 fold or more and can improve the access of small innovative firms to capital during early stages of financing, exactly when such firms lack a track record and information about their potential is less available. It is therefore clear, that any discussion about the value of patents for small innovative firms should include such considerations.

Finally, we note that while the main focus of our work here is not on the impact of regional characteristics and proximity effects on of venture capital financing of firms, our results yielded some additional interesting insights that are worth emphasizing. Proximity effects were found to have a positive impact on the venture capital funds of small biotech firms only during the first round of financing when firms were in the early stages of development. It is therefore possible that knowledge spillovers from agglomeration and associated pecuniary effects may be stronger for smaller firms early in their innovation cycle. Such segment specific effects are not broadly researched in the literature that examines the sources of agglomeration

economies and it may be a worthwhile follow-up research topic.

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Table 1. Descriptive Statistics of Variables Used in the Empirical Models

	Variable name	Observations	Mean	St. Dev	Median	Mode
Total amount of venture capital funded to a biotechnology firm for the first round of investment ($1,000,000)	VCF_Investment_1	1,584	5.65	14.50	2.15	1.00
The total amount of venture capital funded to a biotechnology firm for the second round of investment ($1,000,000)	VCF_Investment_2	1,173	6.92	10.10	3.50	2.00
Number of patent applications filed by a biotechnology firm from foundation to the first round of investment	PATENTApp_1	1,326	0.53	10.57	0.00	0.00
Number of patent applications filed by a biotechnology firm from the first round of investment to the second round of investment	PATENTApp_2	1,092	0.38	1.78	0.00	0.00
Number of patents granted to a biotechnology firm from firm foundation to the first round of investment	PATENTGrant_1	1,327	0.42	7.70	0.00	0.00
Number of patents granted to a biotechnology firm from the first round of investment to the second round of investment	PATENTGrant_2	1,092	0.45	2.79	0.00	0.00
Average number of forward patent citations per year of patents granted between firm foundation and the first round of investment	PATENTCiteYear_1	1,523	0.06	0.46	0.00	0.00
Average number of forward patent citations per year of patents granted between the first round of investment and the second round of investment	PATENTCiteYear_2	1,523	0.11	0.74	0.00	0.00
An index that is increasing with the average reputation score of the participating venture capital firms in the previous investment round[1]	VCFreputation_1	1,762	0.31	0.43	0.00	0.00
Dummy variable which takes the value of 1 if a biotechnology firm founder holds a distinguished and/or named professorship and/or is a member of the Academy of Sciences and/or Nobel Prize and/or had previously founded other firms[2]	FounderSignal	101				
Average sum the funding venture capital firms had raised prior to investing in the focal firm for the first round of investment ($1,000,000)	SyndicateSize_1	1,762	295.24	430.67	80.29	0.00
Average sum the funding venture capital firms had raised prior to investing in the focal firm for the second round of investment ($1,000,000)	SyndicateSize_2	1,762	329.93	403.20	118.00	0.00
Number of venture capital firms participating in the first round of investment	SyndicateInvestors_1	1,762	2.28	1.74	2.00	1.00
Number of venture capital firms participating in the second round of investment	SyndicateInvestors_2	1,275	2.99	2.54	2.00	1.00
Distance of the focal firm to the closest funding participating venture capital firm (miles)	DistanceClosestVCF	1,424	390.01	707.36	26.61	0.04
Total number of universities located in the focal firm's Metropolitan Statistical Area	UniversitiesInMSA	1,762	9.60	9.02	6.00	1.00
Total number of venture capital firms located within 0 to 10 miles from the focal firm founded before the first round of investment	VCFarea_0010_1	1,762	16.05	24.07	5.00	0.00
Total number of venture capital firms located within 10 to 20 miles from the focal firm founded before the first round of investment	VCFarea_1020_1	1,762	10.72	20.47	2.00	0.00
Total number of venture capital firms located within 0 to 10 miles from the focal firm founded before the second round of investment	VCFarea_0010_2	1,762	17.98	26.36	5.00	0.00
Total number of venture capital firms located within 10 to 20 miles from the focal firm founded before the second round of investment	VCFarea_1020_2	1,762	11.80	22.01	3.00	0.00
Total number of patents held by biotechnology firms located within 0 to 10 miles from the focal firm before the first round of investment	PATENTArea_0010_1	1,762	89.46	137.83	23.00	0.00
Total number of patents held by biotechnology firms located within 10 to 20 miles from the focal firm before the first round of investment	PATENTArea_1020_1	1,762	51.18	98.49	9.00	0.00
Total number of patents held by biotechnology firms located within 0 to 10 miles from the focal firm before the second round of investment	PATENTArea_0010_2	1,762	94.34	140.87	26.00	0.00
Total number of patents held by biotechnology firms located within 10 to 20 miles from the focal firm before the second round of investment	PATENTArea_1020_2	1,762	54.39	102.87	11.00	0.00
Age of a biotechnology firm from foundation to the first round of investment (years)	Age1	1,548	3.33	7.34	1.00	0.00
Age of a biotechnology firm from foundation to the second round of investment (years)	Age2	1,187	4.36	8.75	2.42	1.00

[1]The index takes the value of 0 if the participating VCFs are unranked. When participating VCFs are ranked in the the Lee-Pollock-Jin VC Reputation index (Lee, Pollock et al. 2011), the value lies between 1 (when the VCF is rank 1) and 0.001 (when the VCF is the lowest ranked VCF in the list).

[2]In the case of the *FounderSignal* variable the figure measures the number biotechnology firms with the founder matching the said characteristics

Table 2. Estimated coefficients for model of the first round of financing. The Dependent Variable is the natural log of the amount of venture capital funds raised by a biotechnology firm for the first round of financing.

Variable Description	Variable code	Coefficient	Heteroskedasticity robust standard errors	Standard errors clustered at the state level
	Intercept	11.5473	0.2679 ***	0.4349 ***
Number of patent applications filed by a biotechnology firm from foundation to the first round of investment	PATENTApp_1	0.1129	0.0371 ***	0.0359 ***
Number of patents granted to a biotechnology firm from firm foundation to the first round of investment	PATENTGrant_1	-0.0155	0.0466	0.0472
Average number of forward patent citations per year of patents granted between firm foundation and the first round of investment	PATENTCiteYear_1	0.1701	0.0639 ***	0.0603 ***
Dummy variable which takes the value of 1 if a biotechnology firm founder holds a distinguished and/or named professorship and/or is a member of the Academy of Sciences and/or Nobel Prize and/or had previously founded other firms	FounderSignal	0.4336	0.1338 ***	0.1353 ***
Average sum the funding venture capital firms had raised prior to investing in the focal firm for the first round of investment ($1,000,000)	SyndicateSize_1	0.0003	0.0001 ***	0.0002
Number of venture capital firms participating in the first round of investment	SyndicateInvestors_1	0.3790	0.0260 ***	0.0353 ***
Distance of the focal firm to the closest funding participating venture capital firm (miles)	DistanceClosestVCF	0.0003	0.0001 ***	0.0001 **
Total number of universities located in the focal firm's Metropolitan Statistical Area	UniversitiesInMSA	0.0016	0.0056	0.0045
Total number of venture capital firms located within 0 to 10 miles from the focal firm founded before the first round of investment	VCFarea_0010_1	0.0073	0.0020 ***	0.0026 ***
Total number of venture capital firms located within 10 to 20 miles from the focal firm founded before the first round of investment	VCFarea_1020_1	0.0021	0.0025	0.0026
Total number of patents held by biotechnology firms located within 0 to 10 miles from the focal firm before the first round of investment	PATENTArea_0010_1	0.0005	0.0003	0.0002 **
Total number of patents held by biotechnology firms located within 10 to 20 miles from the focal firm before the first round of investment	PATENTArea_1020_1	-0.0002	0.0006	0.0005
Age of a biotechnology firm from foundation to the first round of investment (years)	Age_1	0.0438	0.0108 ***	0.0118 ***
Trend variable that takes the value of 1 for first round investments in 1974 and increases by one unit for every additional year	Trend_1	0.0357	0.0068 ***	0.0162 **
	R^2	0.3259		
	Adjusted R^2	0.3165		
	F-test for overall model significance		36.17 ***	266.76 ***
	Multicollinearity Condition Number	20.125		
	X^2 for Breusch-Pagan test for heteroskedasticity	9.27 ***		
	Number of observations	1020		

*** .01 significance, ** .05 significance

Table 3. Estimated coefficients for model of the second round of financing. The Dependent Variable is the natural log of the amount of venture capital funds raised by a biotechnology firm for the second round of financing.

Variable Description	Variable code	Coefficient	Heteroskedasticity robust standard errors	Standard errors clustered at the state level
	Intercept	12.3852	0.2893 ***	0.2883 ***
Number of patent applications filed by a biotechnology firm from the first round of investment to the second round of investment	PATENTApp_2	0.0289	0.0339	0.0307
Number of patent applications filed by a biotechnology firm from foundation to the first round of investment	PATENTApp_1	0.0353	0.0338	0.0387
Number of patents granted to a biotechnology firm from the first round of investment to the second round of investment	PATENTGrant_2	0.0157	0.0183	0.0159
Number of patents granted to a biotechnology firm from firm foundation to the first round of investment	PATENTGrant_1	0.0234	0.0330	0.0333
Average number of forward patent citations per year of patents granted between the first round of investment and the second round of investment	PATENTCiteYear_2	0.0266	0.0291	0.0336
Average number of forward patent citations per year of patents granted between firm foundation and the first round of investment	PATENTCiteYear_1	0.0116	0.1051	0.1059
Total amount of venture capital funded to a biotechnology firm for the first round of investment ($1,000,000)	VCF_Investment_1	0.0263	0.0054 ***	0.0043 ***
An index that is increasing with the average reputation score of the participating venture capital firms in the previous investment round[1]	VCFreputation_1	-0.0426	0.0957	0.0871
Dummy variable which takes the value of 1 if a biotechnology firm founder holds a distinguished and/or named professorship and/or is a member of the Academy of Sciences and/or Nobel Prize and/or had previously founded other firms	FounderSignal	0.2441	0.1482	0.1469
Average sum the funding venture capital firms had raised prior to investing in the focal firm for the second round of investment ($1,000,000)	SyndicateSize_2	0.0004	0.0001 ***	0.0001 ***
Number of venture capital firms participating in the second round of investment	SyndicateInvestors_2	0.2470	0.0171 ***	0.0191 ***
Distance of the focal firm to the closest funding participating venture capital firm (miles)	DistanceClosestVCF	0.0002	0.0001 ***	0.0001 ***
Total number of universities located in the focal firm's Metropolitan Statistical Area	UniversitiesInMSA	0.0105	0.0055	0.0034 ***
Total number of venture capital firms located within 0 to 10 miles from the focal firm founded before the second round of investment	VCFarea_0010_2	0.0019	0.0020	0.0015
Total number of venture capital firms located within 10 to 20 miles from the focal firm founded before the second round of investment	VCFarea_1020_2	0.0033	0.0022	0.0031
Total number of patents held by biotechnology firms located within 0 to 10 miles from the focal firm before the second round of investment	PATENTArea_0010_2	0.0001	0.0003	0.0002
Total number of patents held by biotechnology firms located within 10 to 20 miles from the focal firm before the second round of investment	PATENTArea_1020_2	0.0005	0.0005	0.0006
Age of a biotechnology firm from foundation to the second round of investment (years)	Age_2	0.0003	0.0107	0.0110
Trend variable that takes the value of 1 for second round investments in 1974 and increases by one unit for every additional year	Trend_2	0.0296	0.0070 ***	0.0097 ***
	R^2	0.3596		
	Adjusted R^2	0.3449		
	F-test for overall model significance		25.04 ***	271.43 ***
	Multicollinearity Condition Number	24.000		
	X^2 for Breusch-Pagan test for heteroskedasticity	19.28 ***		
	Number of observations	845		

[1]The index takes the value of 0 if the participating VCFs are unranked. When participating VCFs are ranked in the the Lee-Pollock-Jin VC Reputation index (Lee, Pollock et al. 2011), the value lies between 1 (when the VCF is rank 1) and 0.001 (when the VCF is the lowest ranked VCF in the list).

*** .01 significance, ** .05 significance

Figure 1. Number of patents granted to biotechnology firms in a 20 miles radius from the focal firm.

+ 0 Patents in a 0 - 20 miles area around the focal firm
● 1 to 5 Patents in a 0 - 20 miles area around the focal firm
● 6 to 10 Patents in a 0 - 20 miles area around the focal firm
● 11 to 50 Patents in a 0 - 20 miles area around the focal firm
● 51 to 100 Patents in a 0 - 20 miles area around the focal firm
● 101 to 200 Patents in a 0 - 20 miles area around the focal firm
● 201 to 400 Patents in a 0 - 20 miles area around the focal firm
● More than 400 Patents in a 0 - 20 miles area around the focal firm

Figure 2. Number of venture capital firms in a 20 miles radius from the focal firm.

+ 0 VCFs in a 0 - 20 miles area around the focal firm

● 1 to 5 VCFs in a 0 - 20 miles area around the focal firm

● 6 to 10 VCFs in a 0 - 20 miles area around the focal firm

● 11 to 20 VCFs in a 0 - 20 miles area around the focal firm

● 21 to 40 VCFs in a 0 - 20 miles area around the focal firm

● 41 to 80 VCFs in a 0 - 20 miles area around the focal firm

● 81 to 120 VCFs in a 0 - 20 miles area around the focal firm

● More than 120 VCFs in a 0 - 20 miles area around the focal firm

Appendix Table 1. Estimated coefficients for model of the first round of financing. The Dependent Variable is the natural log of the amount of venture capital funds raised by a biotechnology firm for the first round of financing. Compared to Table 2, the number of patent applications before 2001 is calculated with a linear trend.

Variable Description	Variable code	Coefficient	Heteroskedasticity robust standard errors	Standard errors clustered at the state level
	Intercept	11.2299	0.2777 ***	0.4253 ***
Number of patent applications filed by a biotechnology firm from foundation to the first round of investment	PATENTApp_1	0.0953	0.0336 ***	0.0313 ***
Number of patents granted to a biotechnology firm from firm foundation to the first round of investment	PATENTGrant_1	0.0016	0.0504	0.0512
Average number of forward patent citations per year of patents granted between firm foundation and the first round of investment	PATENTCiteYear_1	0.1852	0.0673 ***	0.0622 ***
Dummy variable which takes the value of 1 if a biotechnology firm founder holds a distinguished and/or named professorship and/or is a member of the Academy of Sciences and/or Nobel Prize and/or had previously founded other firms	FounderSignal	0.4455	0.1341 ***	0.1375 ***
Average sum the funding venture capital firms had raised prior to investing in the focal firm for the first round of investment ($1,000,000)	SyndicateSize_1	0.0003	0.0001 ***	0.0002
Number of venture capital firms participating in the first round of investment	SyndicateInvestors_1	0.3795	0.0260 ***	0.0351 ***
Distance of the focal firm to the closest funding participating venture capital firm (miles)	DistanceClosestVCF	0.0003	0.0001 ***	0.0001 **
Total number of universities located in the focal firm's Metropolitan Statistical Area	UniversitiesInMSA	0.0022	0.0056	0.0045
Total number of venture capital firms located within 0 to 10 miles from the focal firm founded before the first round of investment	VCFarea_0010_1	0.0073	0.0020 ***	0.0026 ***
Total number of venture capital firms located within 10 to 20 miles from the focal firm founded before the first round of investment	VCFarea_1020_1	0.0022	0.0025	0.0026
Total number of patents held by biotechnology firms located within 0 to 10 miles from the focal firm before the first round of investment	PATENTArea_0010_1	0.0005	0.0003	0.0002 **
Total number of patents held by biotechnology firms located within 10 to 20 miles from the focal firm before the first round of investment	PATENTArea_1020_1	-0.0002	0.0006	0.0005
Age of a biotechnology firm from foundation to the first round of investment (years)	Age_1	0.0446	0.0112 ***	0.0122 ***
Trend variable that takes the value of 1 for first round investments in 1974 and increases by one unit for every additional year	Trend_1	0.0422	0.0069 ***	0.0156 ***
	R^2	0.3247		
	Adjusted R^2	0.3152		
	F-test for overall model significance		36.28 ***	281.1 ***
	Multicollinearity Condition N	20.300		
	X^2 for Breusch-Pagan test for heteroskedasticity	8.66 ***		
	Number of observations	1020		

Appendix Table 2. Estimated coefficients for model of the second round of financing. The Dependent Variable is the natural log of the amount of venture capital funds raised by a biotechnology firm for the second round of financing. Compared to Table 3, the number of patent applications before 2001 is calculated with a linear trend.

Variable Description	Variable code	Coefficient	Heteroskedasticity robust standard errors	Standard errors clustered at the state level
	Intercept	12.1299	0.2945 ***	0.3295 ***
Number of patent applications filed by a biotechnology firm from the first round of investment to the second round of investment	PATENTApp_2	0.0037	0.0268	0.0199
Number of patent applications filed by a biotechnology firm from foundation to the first round of investment	PATENTApp_1	0.0760	0.0366 **	0.0416
Number of patents granted to a biotechnology firm from the first round of investment to the second round of investment	PATENTGrant_2	0.0243	0.0247	0.0238
Number of patents granted to a biotechnology firm from firm foundation to the first round of investment	PATENTGrant_1	0.0205	0.0349	0.0359
Average number of forward patent citations per year of patents granted between the first round of investment and the second round of investment	PATENTCiteYear_2	0.0289	0.0280	0.0325
Average number of forward patent citations per year of patents granted between firm foundation and the first round of investment	PATENTCiteYear_1	0.0009	0.0986	0.0917
Total amount of venture capital funded to a biotechnology firm for the first round of investment ($1,000,000)	VCF_Investment_1	0.0265	0.0053 ***	0.0046 ***
An index that is increasing with the average reputation score of the participating venture capital firms in the previous investment round[1]	VCFreputation_1	-0.0390	0.0956	0.0898
Dummy variable which takes the value of 1 if a biotechnology firm founder holds a distinguished and/or named professorship and/or is a member of the Academy of Sciences and/or Nobel Prize and/or had previously founded other firms	FounderSignal	0.2426	0.1484	0.1557
Average sum the funding venture capital firms had raised prior to investing in the focal firm for the second round of investment ($1,000,000)	SyndicateSize_2	0.0004	0.0001 ***	0.0001 ***
Number of venture capital firms participating in the second round of investment	SyndicateInvestors_2	0.2477	0.0171 ***	0.0196 ***
Distance of the focal firm to the closest funding participating venture capital firm (miles)	DistanceClosestVCF	0.0002	0.0001 ***	0.0001 ***
Total number of universities located in the focal firm's Metropolitan Statistical Area	UniversitiesInMSA	0.0103	0.0056	0.0034 ***
Total number of venture capital firms located within 0 to 10 miles from the focal firm founded before the second round of investment	VCFarea_0010_2	0.0020	0.0020	0.0015
Total number of venture capital firms located within 10 to 20 miles from the focal firm founded before the second round of investment	VCFarea_1020_2	0.0033	0.0022	0.0031
Total number of patents held by biotechnology firms located within 0 to 10 miles from the focal firm before the second round of investment	PATENTArea_0010_2	0.0001	0.0003	0.0002
Total number of patents held by biotechnology firms located within 10 to 20 miles from the focal firm before the second round of investment	PATENTArea_1020_2	0.0005	0.0005	0.0006
Age of a biotechnology firm from foundation to the second round of investment (years)	Age_2	0.0003	0.0106	0.0115
Trend variable that takes the value of 1 for second round investments in 1974 and increases by one unit for every additional year	Trend_2	0.0348	0.0070 ***	0.0103 ***
	R^2	0.3603		
	Adjusted R^2	0.3455		
	F-test for overall model significance		25.32 ***	241.21 ***
	Multicollinearity Condition Number	27.189		
	X^2 for Breusch-Pagan test for heteroskedasticity	19.79 ***		
	Number of observations	845		

[1]The index takes the value of 0 if the participating VCFs are unranked. When participating VCFs are ranked in the the Lee-Pollock-Jin VC Reputation index (Lee, Pollock et al. 2011), the value lies between 1 (when the VCF is rank 1) and 0.001 (when the VCF is the

*** .01 significance, ** .05 significance